

THE CHALLENGE OF MEASURING FINANCIAL STRESS. CASE STUDY FOR IDENTIFYING THE MACROECONOMIC TRIGGERS OF FINANCIAL CRISIS WITH PANEL DATA MODELS

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Abstract

Measuring financial stress is a key research issue that has gained a lot of interest in the years following the extreme events from 2007. Although a lot of models were used for assessing and measuring financial stress, none of the managed to forecast the global crisis from 2007. We can identify three generation of models plus the approach of measuring the probability of a crisis with financial stress indexes. In our paper, we review briefly the most important approaches in measuring financial stress from the specialty literature and we propose a case study for European countries. We apply a logistic regression model for panel data, using macroeconomic indicators with the goal of finding the most important triggers for a financial crisis or otherwise said, the early warning signals of a crisis. We obtain very good accuracy of the proposed model (85%) and the results are of great importance for policy makers and also for researchers. The study highly contributes to the specialty literature, considering that it is the first early warning system developed on macroeconomic indicators only for European advanced and emerging economies. Moreover, it includes in the analysis a period of five year following 2007.

Key words: crisis prediction; early warning systems; global economic crisis; logistic regression; systemic risk;

JEL Classification: C33, G01, C53.

I. INTRODUCTION

The research problem of assessing economic and financial risk has been in the attention of many researchers and practitioners even before the eruption of the global financial crisis in 2007. Many studies have focused on measuring financial stress and the impact on the economy. The studies that focused on predicting the systemic crisis use the country's indicators for determining the significant factors that can help explain crises. Early warning systems allow an advance anticipation for a possible financial crisis, and thus could transform the threats of a crisis into opportunities, if correctly predicted. The importance of correctly foreseeing a crisis is of great interests for many parties: for macro policy makers, that want to find the leading indicators of stress on economic growth; for market participant who want to measure and limit their risk to currency or stock market fluctuations; to financial regulators who want to maintain their equilibrium on the market.

The objective of our paper is to find the macroeconomic indicators that could be the signals of an upcoming financial crisis. We develop a case study only on European countries, approach that hasn't been so far used in the literature. The structure of the paper is as follows: in the next section we review the most used definitions of a financial crisis and its components; in section three we make an overview of the specialty literature regarding the models used for assessing financial risk and the fourth part of the paper is reserved for the Case Study; last section concludes.

II. LITERATURE REVIEW – DEFINITION OF FINANCIAL CRISIS

Many studies for assessing financial stability focus on finding the early warning signals of crisis, but the first thing to establish is the definition of the crises itself. Usually, the crises episode are defined using binary variables on the base of the extreme values of one or more variables. Crises that occur in different markets are considered individually. In the specialty literature, we distinguish between four main type of crisis: banking crisis, exchange market crises, sovereign debt crises or equity market crises.

Banking crises are defined by Kaminsky and Reinhart (1999) as a combination of country-specific events. This qualitative approach has been enriched with quantitative assessment of a crisis situation, for instance by

Demirguc – Detragiache (1998), who define a banking stress situation if at least one of the criteria are met: (1) the ratio of non- performing assets to total assets is higher than 10% ; (2) the cost of the rescue operation is at least 2% of the GDP; (3) banking stress situation are finalized into a large-scale nationalization of banks; (4) emergency measures are drawn by extreme bank runs (Demirguc, 1998). Foreign exchange or currency crises are defined as significant devaluations and/or losses in reserves. The most known definition of a currency crises remains that of Frankel and Rose (1996) who define the currency crisis as a nominal depreciation of at least 25% that is higher than the change of the previous year by a margin of at least 10 pp. The third type of stress episodes mentioned in the specialty literature is the debt crisis – defines as the inability of sovereign nations to service foreign debt (Bordo and Schwartz, 2000). Most of the literature on debt crises is related to a set of emerging economies that have been the subject of extreme indebtiness at the beginning of the 1980s. However, we note that these economies are identified mainly by qualitative information. Finally, equity crisis are defined as a significant decline in the overall market index. In the specialty literature, equity crises are assessed with the CMAX method.

The twin or triple crises are defined by the overlapping of two or three of these types of crises. In the period 1970 – 2011, the banking crisis have been prevalent (146 episodes) and also the currency crises (with a total of 218 episodes), while debt sovereign crisis were reported in 66 situations (Reinhart, Rogoff, 2013). The incidence of twin crisis is lower, as depicted in Figure 1.

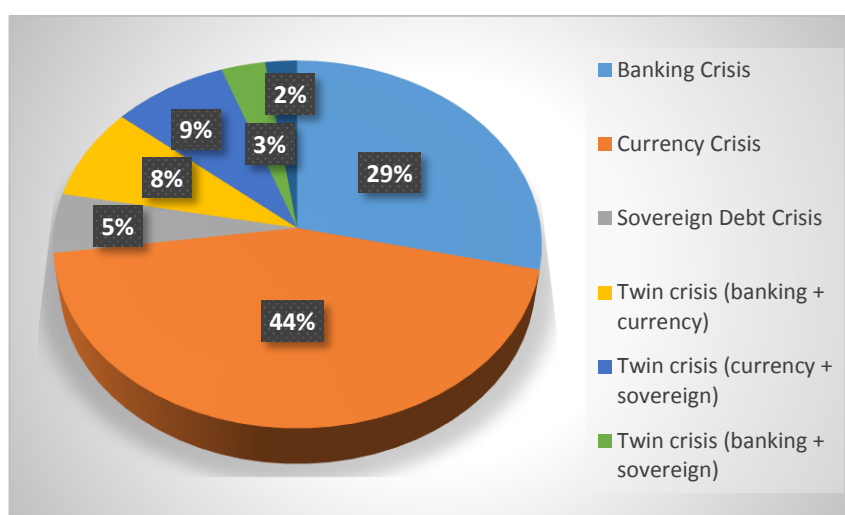


Figure 1 – Distribution of crisis episodes on types of crisis (period 1970 – 2011)

III. AN OVERVIEW OF THE MODELS USED FOR ASSESSING FINANCIAL CRISIS

The literature on financial crises is quite large, numerous models for early warning system have been created. We mention the study of Hanschel and Monnin (2005) who construct a stress index for the banking system in Switzerland with a methodology similar to that of Illing, Liu (2006). They use a combination of market price, balance sheet and other structural variables. However, the forecasts are sensitive to the model specifications.

Illing and Liu (2006) develop a Financial Stress Index for the Canadian financial system, by evaluating sub-indexes for the four risk components: banking risk, currency risk, sovereign risk and equity risk. We also mention the work of Cardarelli et al. (2011) who construct a financial stress index for 17 economies (advanced economies) and study the links between the financial stress episodes and the economic cycle. On the other side, Balakrishnan et al. (2011) constructed an index for developing countries and focused on the vulnerabilities of these economies based on the linkages with the developed ones. The work of Balakrishnan et al (2011) is further developed by Cevik et al. (2013) with specific considerations for the following countries: Bulgaria, the Czech Republic, Hungary, Poland, and Russia. Romania was not considered in the analysis, due to insufficient data. On the financial stress index, we mention also the indexes constructed by Lo Duca and Peltonen (2011) and Hollo et al. (2012) that are basically developed using the same methodology. Five raw stress sub-indicators are aggregated after transforming them on the basis of the quartiles derived from the CDF (Cumulative Distribution Function). The index developed by Hollo (2012) is named CISS – Composite Indicator of Systemic Stress and its aim is to measure the level of systemic risk.

Apart from these Financial Stress Indexes developed, in the specialty literature we find three generation of models of assessing early warning triggers of financial risk. The three generation of models are: the signal Approach, the Regression approach (pooled panel data) and the machine learning methods. Regarding the first generation, the Signal Approach – in this category of models, the individual variables (macroeconomic variables like real exchange rate of debt to GDP levels) are “signals” for indicating that a country is in a potentially state of crisis if a certain threshold is exceeded. However, the models have the disadvantage of being univariate, although a composite index for prediction purposes has been also proposed. This method has been introduced by Kaminsky and Reinhart (1998, 1999). The second generation of models that we mention is based on discrete choice modelling techniques applied to macroeconomic and financial variables for explaining discrete crisis events. These are parametric models, subject to statistical assumption (for instance, Bussiere and Fratzscher, 2006, used this type of model). The third generation of models refers to using neural networks for predicting financial crisis.

IV. CASE STUDY

In the case study, we propose a logistic regression model with the scope of identifying the triggers of a financial crisis and of applying the model for forecasting future possible instability situations.

Firstly, we will describe the database. We develop our model for a set of 27 European countries (and also including Israel, see Table 1), 15 advanced economies and 12 emerging economies. For these economies, we register 10 macroeconomic variables (described in detail in Table 2), chosen upon data availability and based on similar studies in the specialty literature, for allowing comparison of results. Data was taken from World Bank and Euro Stat official websites. In the first column of the table we have the name of the macroeconomic variable, the second column is the metadata and the third column the name given to the variable in the model. We tried to consider a wide variety of variables, by taking into account: the financial aspects of the economy (Domestic Credit, Gross Savings, Market Capitalization, Stocks Traded), the labor force (Unemployment), the economic growth and development (GDP growth, value added in industry, value added in agriculture) and the economic trade (Exports).

The macroeconomic variables are registered on a yearly basis, for a period varying between 1990 and 2012. Data is available for the entire mentioned period only for the advanced economies (on the left in Table 1, the second column depicts the years of data availability). For the emergent economies (the right side of Table 1), data availability starts mostly from 1994 – 1995, considering the transition period of the economies in this category at the beginning of the 1990s. We obtain in the end an unbalanced panel with 27 cross-sections and a total of 574 observations.

Table1. Countries included in the sample/ data availability and year of crisis considered

| Country | Years | Dates of Crisis | Country | Years | Dates of Crisis |
|----------------|-------------|-------------------|-----------------|----------------------------|-----------------------|
| Austria | 1990 – 2012 | 2008 | Bulgaria | 1995 – 1996 1998 – 2012 | 1996 – 1997 ; 2008 |
| Belgium | 1990 – 2012 | 2008 | Czech Republic | 1994 – 2012 | 1996 – 2000; 2008 |
| Denmark | 1990 – 2012 | 2008 | Croatia | 1995 – 2012 | 1998 – 1999 |
| Finland | 1990 – 2012 | 1991 – 1995 | Hungary | 1991 – 2012 | 1991 – 1995; 2008 |
| France | 1990 – 2012 | 2008 | Iceland | 1994 – 2012 | 2008 |
| Germany | 1990 – 2012 | 2008 | Israel | 1990 – 2012 | |
| Greece | 1990 – 2012 | 2008 | Lithuania | 1995 – 2012 | 1995 – 1996 |
| Ireland | 1994 – 2012 | 2008 | Poland | 1991 – 2012 | 1992 – 1994 |
| Italy | 1990 – 2012 | 2008 | Romania | 1994 – 2012 | 2009 |
| Netherlands | 1990 – 2012 | 2008 | Slovak Republic | 1994 – 2012 | 1998 – 2002 |
| Norway | 1990 – 2012 | 1991 – 1993 | Slovenia | 1995 – 2012 | 2008 |
| Portugal | 1990 – 2012 | 2008 | Latvia | 1995 – 2012 | 1995 – 1996; 2008 |
| Spain | 1990 – 2012 | 2008 | | | |
| Sweden | 1990 – 2012 | 1991 – 1995, 2008 | | | |
| United Kingdom | 1990 – 2012 | 2007 | | | |

Table 2. Description of variables (source of metadata: World Bank)

| Indicator | Description | Name of variable in the model |
|--|--|-------------------------------|
| Domestic Credit (% GDP) | Domestic credit provided by the financial sector includes all credit to various sectors on a gross basis, with the exception of credit to the central government, which is net. | domestic_credit |
| GDP growth | Annual percentage growth rate of GDP at market prices based on constant local currency. | gdp_growth |
| Gross Savings (% GDP) | Gross savings are calculated as gross national income less total consumption, plus net transfers. | gross_sav |
| Industry Value Added (% GDP) | Industry comprises value added in mining, manufacturing, construction, electricity, water, and gas. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. | industry_va |
| Agriculture, value added (% of GDP) | Agriculture corresponds to ISIC divisions 1-5 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production. | agriculture_va |
| Inflation | Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. | Inflation |
| Market capitalization (% GDP) | Market capitalization (also known as market value) is the share price times the number of shares outstanding. | market_cap |
| Stocks Traded (% GDP) | Stocks traded refers to the total value of shares traded during the period. This indicator complements the market capitalization ratio by showing whether market size is matched by trading. | stocks_value |
| Unemployment | Unemployment refers to the share of the labor force that is without work but available for and seeking employment. | unemployment |
| Exports of goods and services (% of GDP) | Represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services. | Exports |

The dependent variable considered in the model is a binary variable – the presence or the absence of a systemic crisis for each year registered on every economy in the sample.

We use the definition of a systemic crisis introduced by Leaven, Fabian (2013), who state that a banking crisis is systemic if two conditions are met: "1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations) 2) Significant banking policy intervention measures in response to significant losses in the banking system" (Leaven, Fabian, 2013, page 4).

The first year when both criteria are met is the year when the banking crises becomes systemic. Regarding the second criteria, the policy interventions in the banking sector are considered significant if at least three out of the following six measures have been used: "1) extensive liquidity support (5 percent of deposits and liabilities to nonresidents) 2) bank restructuring gross costs (at least 3 percent of GDP) 3) significant bank nationalizations 4) significant guarantees put in place 5) significant asset purchases (at least 5 percent of GDP) 6) deposit freezes and/or bank holidays." (Leaven, Fabian, 2013, page 4).

In Table 1, on the third column we have the years when each economy was declared in a systemic crises, as mentioned in the database of Leaven, Fabian (2008 and update from 2013). We note some particularities of the data. The first observation is that almost all economies in the sample are reported in a crisis in 2008 (United Kingdom since 2007) and at 2012, which is the last year available in the database that we used, the crisis was still ongoing. The exception of the 2008 crisis are two Nordic countries: Finland and Norway (reported in crisis only at the beginning of 1990s when faced with the strong Nordic countries crisis); Croatia (crisis in 1998 – 1999), Lithuania (crisis in 1995 – 1996), Poland (crisis 1992 – 1994), Slovak Republic (crisis between 1998 – 2002) and Israel that was not reported in a crisis in the period 1990 – 2012. We also note that start year of systemic crisis due to the global financial crisis is 2009 (not 2008 as for the others economies in the sample).

With the variables depicted in Table 2 and the dependent variable described above, for the panel data that we explained (with details in Table 1), we estimate a panel logistic regression model, with random effects (software used was Stata 13) whose results are found in Fig. 2. We mention that the fixed effects model was also tested, but the variables were not significant, model was invalid, meaning that the random effects are present in the data, and we have significant differences between the cross-sections. In what follows we will comment the results obtained from the model.

| Log likelihood = -179.09509 | | Wald chi2(10) = 90.12 | | Prob > chi2 = 0.0000 | |
|-----------------------------|-----------|-----------------------|-------|----------------------|----------------------|
| bc | Coef. | Std. Err. | z | P> z | [95% Conf. Interval] |
| gdp_growth | -.2401113 | .0581685 | -4.13 | 0.000 | -.3541195 -.1261031 |
| exports | .0584833 | .0157025 | 3.72 | 0.000 | .027707 .0892595 |
| stocks_value | .0155513 | .0069445 | 2.24 | 0.025 | .0019404 .0291622 |
| inflation | .0064668 | .0102695 | 0.63 | 0.529 | -.013661 .0265946 |
| domestic_credit | .0463094 | .0078602 | 5.89 | 0.000 | .0309036 .0617151 |
| market_cap | -.0800015 | .0145644 | -5.49 | 0.000 | -.1085471 -.0514559 |
| gross_sav | -.127539 | .0562874 | -2.27 | 0.023 | -.2378604 -.0172176 |
| industry_va | -.1338953 | .0486747 | -2.75 | 0.006 | -.2292961 -.0384946 |
| unemployment | .1820774 | .0589013 | 3.09 | 0.002 | .0666329 .2975218 |
| agriculture_va | -.1316959 | .1088006 | -1.21 | 0.226 | -.3449412 .0815495 |
| /lnsig2u | 1.40265 | .4468003 | | | .526938 2.278363 |
| sigma_u | 2.016423 | .4504692 | | | 1.301437 3.12421 |
| rho | .5527537 | .1104566 | | | .3398619 .7479136 |

Likelihood-ratio test of rho=0: **chibar2(01) = 43.26 Prob >= chibar2 = 0.000**

Figure 2 – Model output for the Logistic Regression (binary output variable) – initial model

From Fig. 2 (initial model), we first notice the significant variables. We find that the variables: GDP growth, Exports, Domestic Credit, Market Capitalization, Value added in industry and Unemployment are significant at a 99% confidence level, whereas Stocks value and Gross savings are significant at 97% confidence level, so these variables could be considered the significant triggers of the probability of a crisis. However Inflation and the Value added in agriculture are not significant variables in the model (with p-values higher than the 0.05 or even 0.1 threshold). As a result, we can draw the first conclusion of our model: Inflation and the Value added in agriculture are not triggers or early-warning signals for a financial crisis. We re-estimate the model, keeping only the significant variables and find the results from Fig. 3.

| Log likelihood = -181.72904 | | Wald chi2(8) = 93.03 | | Prob > chi2 = 0.0000 | |
|-----------------------------|-----------|----------------------|-------|----------------------|----------------------|
| bc | Coef. | Std. Err. | z | P> z | [95% Conf. Interval] |
| gdp_growth | -.2594166 | .0566427 | -4.58 | 0.000 | -.3704342 -.148399 |
| exports | .0631747 | .0156267 | 4.04 | 0.000 | .032547 .0938025 |
| stocks_value | .0150425 | .0068732 | 2.19 | 0.029 | .0015713 .0285138 |
| domestic_credit | .0465096 | .0077015 | 6.04 | 0.000 | .0314151 .0616042 |
| market_cap | -.0778687 | .014191 | -5.49 | 0.000 | -.1056825 -.0500548 |
| gross_sav | -.1194247 | .0542992 | -2.20 | 0.028 | -.2258491 -.0130003 |
| industry_va | -.1592385 | .0439445 | -3.62 | 0.000 | -.2453682 -.0731087 |
| unemployment | .1599584 | .0555805 | 2.88 | 0.004 | .0510226 .2688942 |
| /lnsig2u | 1.444189 | .444734 | | | .5725266 2.315852 |
| sigma_u | 2.058741 | .4577961 | | | 1.331443 3.183324 |
| rho | .5629989 | .1094184 | | | .3501634 .7549158 |

Likelihood-ratio test of rho=0: **chibar2(01) = 45.66 Prob >= chibar2 = 0.000**

Figure 3 – Output of the final Model for the Logistic Regression (binary output variable)

From the output of the final model (Fig. 3), we now observe that all the variables are significant (p-values under 0.05 and 0.00 for half of the variables in the model). We will now refer to the sign of the estimated coefficients. We find that GDP growth, Market Capitalization, Gross Savings and Value added in Industry have negative coefficients, meaning an inverse relationship between these variables and the probability of a financial crisis. This is, as we can observe, in concordance with the economic theory. Higher value of GDP growth, Market capitalization, Savings, Value added in industry translate into a healthy economy, with a growing, industrialized and wealthy macroeconomic environment. These are the premises for a low probability of a crisis. A deterioration of these indicators would indicate an increase in the probability of a crisis, thus these variables would be early warning triggers for a financial crisis. On the others side, we have the coefficients with the positive signs: Exports, Value of Stocks, Domestic Credit and Unemployment. The increased value in Stocks and in the Domestic Credit is associated with higher probabilities of a financial crisis. This is due mainly by the

fact that most of the crises considered in our study were episode from 2008, which was in particular a crisis of the Credit boom and of the expansive increases on the stocks markets. This means that increasing value of the two indicators are early warning indicators for financial stress situations. The same comment applies for unemployment, only that this indicator characterize the labor force market, while the previous two indicators could be associated with the financial market. Finally, Exports register also a positive correlation with the probability of a crisis. Actually, this may contradict the economic theory that considers exports a determinant of economic growth. However, this is a particularity of the model, and because in our analysis, we have considered only European countries, the variable Exports can be associated with the "contagion effect" in a crisis situation, especially considering the significant trading relations between the economies in Europe. The Exports variable is a quantification of the "domino" effect specific to the global financial crisis erupted in 2007. As a conclusion of the model output, we notice the variables with the highest significance, thus the most powerful early warning triggers of a financial crisis: the Domestic Credit, GDP growth and Market capitalization.

Table 3. In-sample accuracy of the model

| | Real output crisis | Real output no-crisis |
|-----------------------------------|---------------------------|------------------------------|
| Predicted output crisis | TP (true positive) = 86 | FP (false positive) = 36 |
| Predicted output no-crisis | FN (false negative) = 51 | TN (true negative) = 401 |

After analyzing the results of the estimated model, in terms of coefficients and early warning triggers for the probability of a financial crisis, we focus on the accuracy of the model. As seen in Table 3, the overall in-sample accuracy prediction of the model is 85%. The false negative rate of the model is 9%, the model fails to predicts 51 events of crisis (with an estimated probability of crisis under 50%). On short, the crisis events that are not correctly identified by the model are: crisis in Croatia in 1998 – 1999; crisis period in Czech in the time-frame 1996 – 2000 and 2009 – 2012; Finland, Norway and Sweden in 1993 – 1995; France, Germany, Sweden and Romania from 2010 to 2012; Latvia and Lithuania from 1995 – 1996. The model classifies correctly the rest of approximate 90 crisis events. The reason for which the model fails to predict the mentioned events may have two reasons: the model registers the economy as "recovered" based on the macroeconomic indicators' values for the periods (this could be the case for France, Germany, Sweden) or there are some variables not considered in the model that could trigger the systemic crisis (this could be the case for the Nordic countries – the crisis at the beginning of the 1990s were mainly currency crisis, which have not been quantified in the model). These comments suggest further improvement of the model. However, we note the very good accuracy ratio of 85%, which is in line with the findings from the literature (for instance, Bussiere and Fratzscher, 2006).

V. CONCLUSION

In the present paper, we proposed a case study for finding the best indicators that could be used as early warning signs for a financial stress situation, in the case of European countries. We find that Domestic Credit, GDP growth and Stocks traded are the most important indicator for financial stress, while the exports are a determinant of the contagion effect for the European economies. The study enriches the specialty literature, being the first study to apply the discrete type of model to European data (advanced as well as emerging economies) for addressing financial risk. The article could be further developed by comparing the results with a model obtained from machine learning techniques like neural networks or by enlarging the set of macroeconomic indicators used.

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